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Modelling the Potential Impacts of Climate Change on Rice Cultivation in Mekong Delta, Vietnam

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Received: 28 October 2020; Accepted: 16 November 2020; Published: 18 November 2020

Abstract: Rice paddy fields, considered as a human-made wetland ecosystems, play important roles in food production and ecosystem conservation. Nowadays, rice cultivation in the Mekong Delta, Vietnam, is under severe threat from climate changes, yet there is a shortage of documented information and research on rice production under future climate. Hence, the present study investigates the impacts of climate change on rice cultivation in the MD using an ensemble-modelling approach, implemented by biomod2 platform in R software. Rice cultivation occurrence points, eco-physiological and bioclimatic data were utilised to model habitat suitability for rice cultivation under current and future climate, RCP 4.5 and RCP 8.5 scenarios of the year 2050. The ensemble model obtained acceptable accuracy with scores of 0.880, 0.993 and 0.960 for KAPPA, ROC/AUC and TSS, respectively. Simulation results show that the mean loss of suitable land and mean gain of unsuitable land were 31.4% and 64.6%, respectively, for the year 2050 compared to the present. Salinity intrusion, increases in precipitation during rainy season and decreases in precipitation during dry season were key factors driving the loss of suitable habitat. The findings of this study critically support policy makers and planners in developing appropriate strategies for adaptation and mitigation in response to climate change for sustainable rice cultivation.

Keywords: climate change; sustainability; sea level rise; Mekong Delta; rice habitat suitability; ensemble modelling

1. Introduction

Rice paddy is considered a human-made wetland according to the Ramsar Classification System and is the second largest wetland type around the world [1]. Apart from the important role in food production, this wetland type delivers critical ecological services for related water resources and large agrobiodiversity [2]. Rice paddy fields can function not only as shallow reservoirs to reduce surface runoff during wet periods and supply drainage water for dry periods [1], but also as treatment wetlands to purify water [3]. Rice paddy fields also provide regional fauna and flora biodiversity as well as wild life habitats [4–6]. Therefore, appropriate use, maintenance and rehabilitation of human-made wetlands, particularly rice paddy field resources, are recommended for ecosystem protection and food production [1].

Alongside the critical ecosystem functions mentioned above, rice paddy fields in the Mekong Delta (MD) in Vietnam play an important role in food production and the broader economy of the country. Agricultural land accounts for 64% of total land in the MD [7], and rice is the dominant crop, with a cultivated area of 73.9% of the agricultural land [8]. The MD is considered as the "rice bowl of Vietnam", providing approximately 57% of national rice production and supplying the rice export industry with 90% of total export volume of Vietnam [9,10]. The domestic and export market for rice from the MD contributes a fifth to GDP of the country [8].

Rice cultivation is highly susceptible to climate fluctuations and hence to anthropogenic global climate change [11,12]. In the MD, climate change is threatening agriculture, especially rice cultivation through various pathways [8,13–16]. Climate change in the region can cause changes in environmental conditions, such as (1) temperature increases, especially extreme events such as heat waves; (2) changes in rainfall seasonality and the frequency and intensity of floods and droughts; and (3) sea level rise (SLR), which can directly inundate rice cultivation areas and exacerbate saline intrusion. These changed environmental conditions are likely to affect rice growth and so reduce the rice yield and limit suitable lands for rice cultivation [13,14,17,18]. Indeed, higher frequency and intensity of floods and droughts combined with salinity intrusion in recent years have already undermined rice crop production in the MD, subsequently threatening food security [13,17]. Hence, it is important to project the changes in the suitability of land for rice cultivation under climate change at the regional scale in order to develop appropriate adaption and mitigation strategies for food security for the country. Critically, maintaining and rehabilitating rice field habitat also contributes to ecosystem protection and conservation.

Recently, various modelling programs have been developed to analyse climatic suitability of land areas for natural species and communities and crop production under climate change based on advanced GIS and remote sensing techniques [19]. Among the different modelling approaches, species distribution models (SDMs) as empirical tools have the capacity to predict species distribution by correlating geo-localised species data with environmental variables [20]. SDMs can aid not only in identifying suitable conditions for species presence under current climate conditions, but also in predicting potential spatial and temporal distributions of species under various climate conditions [21,22]. Thus, SDMs have been widely used in ecology and natural resource management [20], such as assessment of invasive species risks, predictions of biodiversity and establishment of suitable locations for species cultivation under various climate change scenarios [23–27]. Recently, numerous studies have indicated the potential of SDMs in predicting either the potential distribution of agriculture crops [28–32] or the impacts of climate change on agriculture crops by combining SDMs with general circulation models (GCMs) [31,33–36].

The application of single-algorithm models has been increasingly debated in the SDM literature [27] due to very high variation in predictive performance in comparison to other models [37]. Hence, it is recommended to use multi model approaches, in particular ensemble models, to enhance the robustness of model predictions and their interpretation [38]. Recent studies, which have compared ensemble-modelling approaches to single-algorithm models [39–46], have indicated that the predictions of ensemble models are significantly enhanced in comparison those of single models in terms of model rules.

SDMs, in particular ensemble modelling approaches, have not yet been utilised for the management of rice paddy fields and rice cultivation in the MD. Most of the recent studies, such as Son et al. [13], Karila et al. [47], Nguyen et al. [8], Kontgis et al. [48], Chen et al. [49], Phan et al. [50], Clauss et al. [51], Minh et al. [52], Phung and Nguyen [53], Phung et al. [54] and Hoang-Phi et al. [55], have mainly focused on mapping current spatial distribution of rice cultivation areas using remote sensing data in which the influence of environmental variables on rice cultivation are not adequately taken into account. Despite the important role of rice paddy fields in ecosystems and in rice production in the MD, the literature shows that there has been little research on the future climatic suitability of the region for rice cultivation.

As a step towards addressing these research gaps, the present study aims to evaluate the potential impacts of climate change on the suitability of habitat for rice cultivation utilising an ensemble model including nine single-algorithms that were implemented in biomod2 modelling framework in R software [56]. The specific objectives of this study are to: (1) determine the potential impacts of environmental variables on rice cultivation; (2) model the current and projected future suitability for rice cultivation under two climate scenarios (RCP 4.5 and RCP 8.5) for the years 2050; and (3) identify the potential changes to the suitability of land within the MD for rice cultivation. The study findings will provide essential information to develop management, mitigation and adaptation strategies for rice paddy field ecosystems and rice production in the MD.

2. Materials and Methods

2.1. Study Area

The study area was the MD, which is located in the southwest region of Vietnam, between 8.5°–11.5° N and 104.5°–106.8°E, covering an area of 40,577 km^2 (Figure 1). The MD has a humid tropical monsoon climate, which is characterised by the distinct two seasons, the dry season (December to April) and the rainy season (May to November). The mean annual temperature is 27 °C, and mean annual rainfall is approximately 1800 mm, of which greater than 90% occurs within the rainy season [17]. The MD is a flat and low-lying region with an elevation range of 0–4 m above mean sea level, and so is extremely vulnerable to the climate change impacts of SLR [57,58].

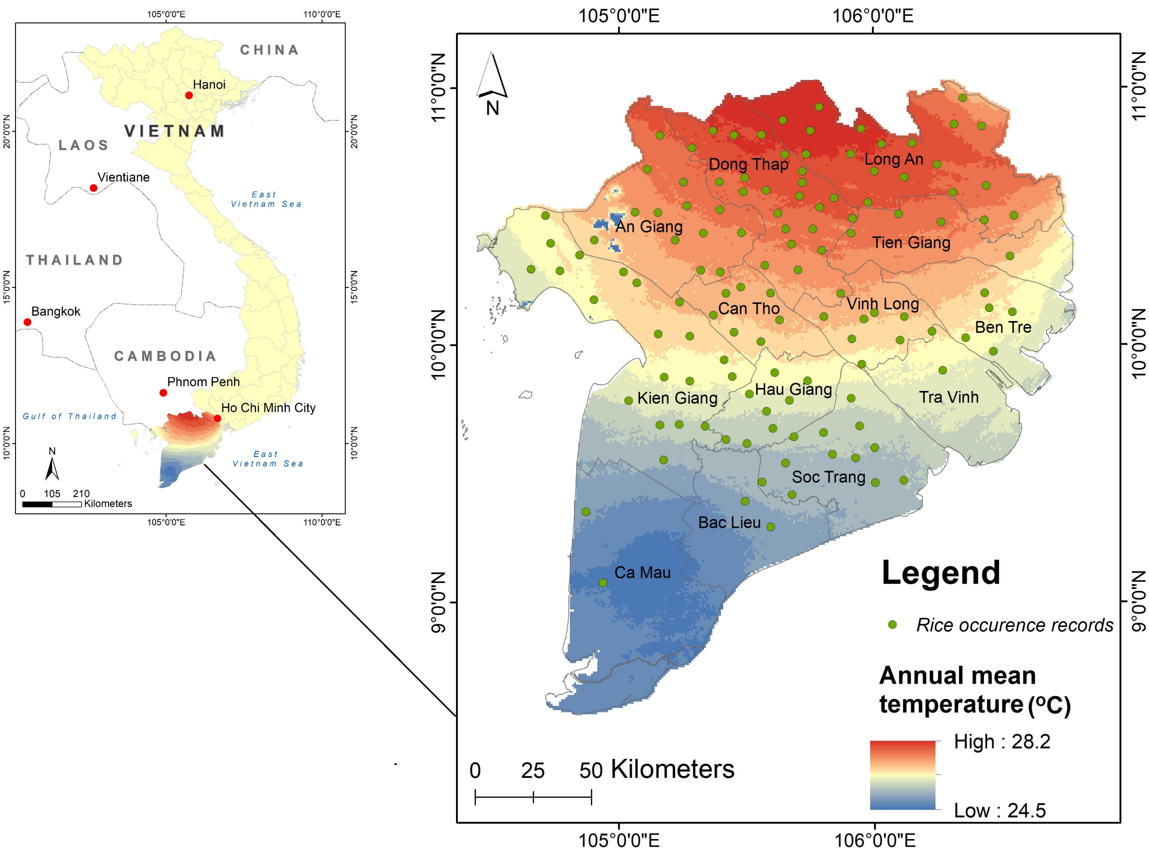

Figure 1. Study area with rice occurrence records, annual mean temperature gradients and provinces in Mekong Delta.

In the MD, rice can be cultivated in three different crops: (1) Đông-Xuân or Spring (November to March); (2) Hè -Thu or Autumn (April to August); (3) Thu-Đông or Winter in inland areas (August to December) and Mùa or Main wet season in coastal areas (July to February) [8]. These three crops appear in different combinations and so result in one to three rice harvests per year, versus single cropped areas (only cultivation during the Main wet season crop), double cropped areas (Spring + Autumn or Autumn + Winter/Main wet season) and triple cropped areas (Spring + Autumn + Winter/Main wet season) [14]. Single cropped areas accounted for only a very small proportion (around 1.26%) of total rice cultivation areas according to the current rice paddy map obtained from MARD (Ministry of Agriculture and Rural Development). Winter and Autumn crops are the two key crops, which provide the majority of rice in the region [8,13], normally referred to as double cropped areas. Triple-cropped areas generally have environmental conditions suitable for double cropped strategy; however, to increase rice production, the triple cropped strategy employs a short Spring-Summer season between Winter-Spring and Summer-Autumn [8]. Hence, the current study mainly considers the suitable lands for the double-cropped and triple-cropped strategies.

2.2. Methodology

Overall, the present study developed an ensemble model to map the potential distribution of rice under current and future climate, based on bioclimatic and ecological variables. Subsequently, the suitability of habitat for rice cultivation in response to the corresponding climate scenarios was determined by masking out the areas with unsuitable salinity level (for rice development) and SLR induced inundation from the maps of rice distribution. A spatial data analysis followed to identify the changes of rice habitat suitability. A brief description of method of the present study is shown in Figure 2.

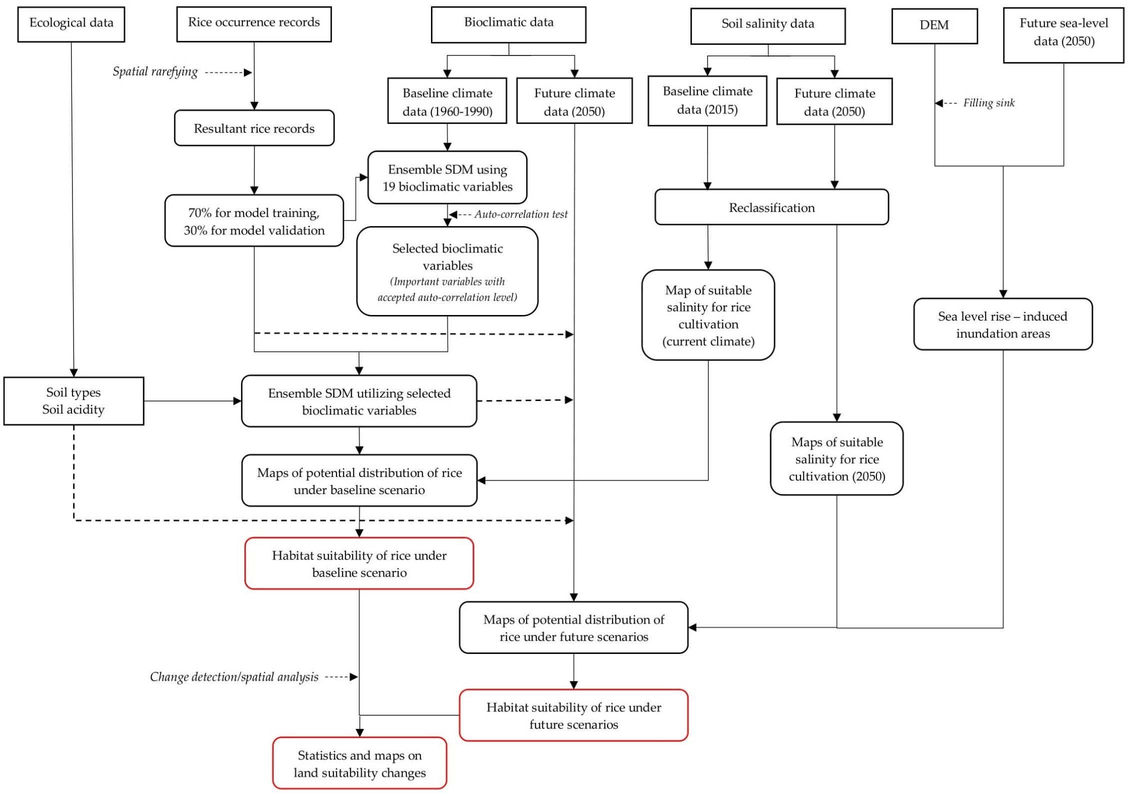

Figure 2. Method flowchart. SDM, species distribution model; DEM, digital elevation model.

2.2.1. Data Compilation

Rice Occurrence Data

Location points represent species occurrence in an environmental space with geographic coordinates (longitudes and latitudes), confirming the species' presence for running the model [35]. Location points where rice is cultivated are hereafter referred to as rice occurrence points. In the present study, rice occurrence points were derived from the observation of rice-growing areas in the MD from the map of rice cultivation areas obtained from the Ministry of Agriculture and Rural Development, Vietnam. The rice cultivation areas from the map were updated until 2018 using surveys, so it is a reliable source of rice occurrence points with similar accuracy level as the survey method. Since our study considered the suitable lands for double and triple cropped strategies, rice occurrence points were extracted from double and triple cropped areas of the map. Through this process, 1187 rice occurrence points were extracted, followed by a manual verification using Google Earth Pro (Version V7.3.3.7786). The Google Earth platform provides high spatial resolution and latest satellite images, and hence is suitable for identifying rice cultivation areas. The location accuracy of the rice records was manually verified by visual checks. This task eliminated 115 rice occurrence points that could not be verified in recent satellite images. It should be noted that various times of satellite images were used for validating rice occurrence points according to their availability in Google Earth; however, these images ranged from May 2019 to February 2020. This period matched with the main rice crops in the MD. To reduce the issue of spatial sampling biases caused by multiple auto-correlated locations [21,59], the rice occurrence points were spatially rarefied at 10 km of maximum user distance [32,60] using SDM toolbox in ArcGIS (version 10.4.1). The final rice occurrence dataset used for building SDMs included 125 rice occurrence records. Figure 1 presents the final rice occurrence records utilised for the modelling exercise.

Environmental Variables

Bioclimatic data including 19 variables (Table 1) were acquired from the Global Climate website (https://worldclim.org/data/bioclim.html) for our current climate (1960–1990) and projected climate data for the year 2050. The data is in grid-based format with a spatial resolution of ~1 km (30 arc-seconds) [61]. Projection of future climate includes the downscaled data of general circulation model (GCM) from the coupled model inter-comparison project (CMIP5). An appropriate combination of different GCMs can improve the consistency of projected climate variables [62,63]. Hence, we combined the three GCMs, including GFDL-CM3 [64], MRI CGCM3 [65] and CNRM CM5 [66], in this study. The combination of the three GCMs was used for the projections of climate in Vietnam [67] and has been used in previous studies in the MD and in South Asia [43,44].

Table 1. Variables (in bold texts) used for predicting the habitat suitability of rice in Mekong Delta.

Category	Sources	Variables	Abbreviations	Units
	For ensemble model to predict potential distribution of rice			
Bioclimatic	WorldClim—Global Climate Data http://www.worldclim.org/	Annual mean temperature	BIO1	°C
		Mean diurnal range	BIO2	°C
		Isothermality	BIO3	Unitless
		Temperature seasonality	**BIO4**	**Unitless**
		Max. temperature of warmest month	**BIO5**	**°C**
		Min. temperature for coldest month	**BIO6**	**°C**
		Temperature annual range	BIO7	°C
		Mean temperature of wettest quarter	BIO8	°C
		Mean temperature of driest quarter	BIO9	°C
		Mean temperature of warmest quarter	BIO10	°C
		Mean temperature of coldest quarter	BIO11	°C
		Annual precipitation	BIO12	mm
		Precipitation of wettest month	**BIO13**	**mm**
		Precipitation of driest month	**BIO14**	**mm**
		Precipitation seasonality	**BIO15**	**Unitless**
		Precipitation of wettest quarter	BIO16	mm
		Precipitation of driest quarter	BIO17	mm
		Precipitation of warmest quarter	BIO18	mm
		Precipitation of coldest quarter	**BIO19**	**mm**
Ecological	FAO www.fao.org/geonetwork	**Soil type**		**Unitless**
	MARD, Vietnam	**Soil acidity**		**Unitless**
	For analysis to delineate the final maps of rice habitat suitability			
	MARD, Vietnam	**Saline concentration**		**(g/L)**
	MONRE, Vietnam	**Sea Level Rise**		**m**

The study projected future climate using the medium emission Representative Concentration Pathway (RCP 4.5) and the high emission Representative Concentration Pathway (RCP 8.5) scenarios for the year 2050. RCP 4.5 represents the intermediate scenario in which emissions peak in 2040 and fall thereafter. RCP 8.5 represents a very high emissions scenario in which emissions grow until 2100 [68].

It is recommended to include non-climatic variables to enhance the predictive performance of SDMs [69,70]. Hence, we included two eco-physiological variables—soil type and soil acidity—that have considerable influence on rice cultivation in the MD [71–73]. The soil type data was acquired from the UN FAO Digital Soil Map of the World V3.6 (http://www.fao.org/geonetwork/), and soil acidity from mapping by the Department of Survey and Mapping, Vietnam. These raster layers had high spatial resolution, so we resampled them to the same ~ 1 km^2 spatial resolution as the bioclimatic raster, using resampling tool in ArcGIS 10.4.1. After this process, 21 predictor variables (see Table 1) as spatial data layers were created, and all layers had the same spatial resolution, extent and projection for initial modelling to identify important variables for further model of potential distribution of rice in the MD.

Saline intrusion also affects rice cultivation in the MD considerably [13,17,74]. Thus, we also used soil salinity data in response to the current climate, and projected soil salinity for RCP 4.5 (with projected SLR of 22 cm) and RCP 8.5 (with projected SLR of 25 cm) scenarios for 2050, in order to predict rice habitat suitability for the corresponding scenarios. The current soil salinity map, which was obtained from the MARD (Ministry of Agriculture and Rural Development), Vietnam, was updated by survey methods in 2015. The projected soil salinity for RCP 4.5 and RCP 8.5 scenarios for 2050 were acquired from Hai et al. [75] and MARD (Ministry of Agriculture and Rural Development) [76], respectively.

Sea level rise (SLR) can inundate the MD and so affects the suitability of habitat for rice cultivation [13,18]. Hence, we used DEM (digital elevation model) to identify areas likely to be inundated due to SLR under the RCP 4.5 and RCP 8.5 scenarios by 2050. The DEM with spatial resolution of 5 m, which was produced by combination of survey points and Aerial imagery by MONRE (Ministry of Natural Resources and Environment), Vietnam, was used for SLR projections as well as other studies of SLR impacts in the country [67].

2.2.2. Rice Habitat Suitability Modelling

Ensemble Model Design for Predicting Potential Distribution of Rice

The biomod2 package in R software [56], which provides a platform for either ensemble prediction of species distribution, or evaluating the influence of environmental variables on species, has advantages over other programs, such as fitting, comparison and ensemble single models. Hence, the present study applied the ensemble modelling approach with this package to model potential distribution of rice, in which nine different single algorithms were used. These single-algorithm models consisted of surface range envelope (SRE) [77], Maxent (MAXENT.Phillips) [78], generalized linear model (GLM) [79], multivariate adaptive regression splines (MARS) [80], flexible discriminant analysis (FDA) [81], classification tree analysis (CTA) [82], artificial neural network (ANN) [83], generalized boosted models (GBM) [84] and random forest (RF) [85].

Pseudo-absence data (background samples) contribute to the enhancement of predictive model performance [86,87]. In the current work, the pseudo-absence samples were created randomly based on environmental variables using R software for model use. Regarding data arrangement for modelling practice, the common trend in the biomod2 platform is to divide the original dataset into two subsets, one to calibrate the model, and the other to validate them [56]. In the present study, we randomly selected 70% of rice occurrence data for model calibration and utilised the remaining 30% for validation. The calibration and validation processes were repeated 10 times to achieve a robust estimation of model performance. We used simple correlation method in biomod2 package to identify the importance of each predictor variable on the climatic niche of rice cultivation. The return score is the result of the subtraction between the calculated correlation values (between variables) and 1. Higher values indicate the variable has greater influence on the model [56].

To identify suitable predictor variables, which have either an important contribution to the potential distribution of rice or acceptable correlation values, we used the 19 bioclimatic variables to run the initial model. Through this process, we determined seven suitable bioclimatic variables (variables in bold text in Table 1) for climatic niche of rice model. These variables were temperature seasonality

(BIO4), maximum temperature of warmest month (BIO5), minimum temperature for coldest month (BIO6), precipitation of wettest month (BIO13), precipitation of driest month (BIO14), precipitation seasonality (BIO15) and precipitation of coldest quarter (BIO19). These bioclimatic variables were considered as important predictors of rice distribution and have acceptable correlation values, i.e., variance inflation factor (VIF) < 10 [88,89] and Pearson correlation coefficient < 0.7 [90]. Subsequently, the seven variables together with two ecological variables, soil type and soil acidity were used to predict the potential distribution of rice using ensemble model using the above design. To obtain a robust prediction of model performance, models were computed with ten replications.

For the assessment of single model accuracy, we used three common evaluation methods, the receiver operating characteristics (ROC/AUC), the Cohen's Kappa (KAPPA) and the true skill statistic (TSS). The details of each evaluation methods are shown in Table 2.

Table 2. Values of three evaluation methods, the Cohen's Kappa (KAPPA), receiver-operating characteristics (ROC/AUC), and the true skill statistic (TSS).

Evaluation Methods	Value Ranges	Performance				References
		Excellent	Good/ Fair/ Useful/	Poor	No Better than Random	
KAPPA	−1 to +1	> 0.75	0.4–0.75	< 0.4		[91]
ROC/AUC	0 to +1	> 0.9	0.7–0.9	0.5–0.7	< 0.5	[92]
TSS	−1 to +1	> 0.8	0.5–0.8	0.2–0.5	< 0.2	[93]

It is difficult to choose the most suitable evaluation method for development and evaluation of ensemble model, due to the lack of consensus on this issue [41]. However, previous studies show the potential of combining ROC and TSS evaluation methods [44,45]. Hence, the present study considered the ROC and TSS scores of single models to develop an ensemble model for rice distribution prediction, in which only the single algorithms with a ROC score > 0.75 [44], and TSS > 0.5 [34,94] were incorporated in the ensemble model. This ensemble model was utilised to model the current and future potential distributions of rice. Areas within the projected maps of potential distribution of rice were categorised in four groups using the reclassify tool in ArcGIS 10.4.1: optimal suitability (value >0.6), moderate suitability (0.4–0.6), low suitability (0.2–0.4) and unsuitable (<0.2).

Evaluation of Salinity and SLR for Rice Habitat Suitability

The salinity map for current climate and projected salinity maps for RCP 4.5 and RCP 8.5 for 2050 were used to refine the rice habitat suitability mapping. Saline concentration greater than 4 g/L is likely to affect rice growth [17,95]. Therefore, the "reclassify" tool in ArcGIS 10.4.1 was used to classify the salinity maps into two categories, including suitable salinity (values <= 4 g/L, value 0) and unsuitable salinity areas (> 4 g/L, value 1) for rice cultivation. The three salinity maps are shown in Figure S1 (in Supplementary material).

The present study used the DEM to identify the SLR-induced inundation areas according to RCP 4.5 and RCP 8.5 of the year 2050 with sea level rises of 22 cm and 25 cm, respectively [67]. The DEM data from MONRE, Vietnam, had numerous sinks representing negative values by pixels, and so could result in problems for further use. Hence, the sinks were eliminated by modifying the negative values with improved values employing the "fill" tool in ArcGIS (version 10.4.1) [96], and so a depressionless DEM was generated. Subsequently, SLR induced inundation areas in response to RCP 4.5 and RCP 8.5 of the year 2050 were generated using the Raster Calculator in ArcGIS 10.4.1. For RCP 4.5, areas (pixels in the DEM) with elevation below 22 cm were identified as inundation areas. Similarly, for RCP 8.5, areas with elevation less than 25 cm were inundated. These inundation areas were categorised into value 1, other areas had value 0. Maps of SLR induced inundation areas for the two future climate scenarios are illustrated in Figure S2 (in Supplementary material).

The salinity and inundation maps were converted to polygons for further analysis using the "raster to polygon" tool in ArcGIS 10.4.1. On the basis that the areas with value salinity of 1 and/or inundation value of 1 (as per definition above) were unsuitable for rice growth. Hence, these unsuitable areas were masked out from potential distribution of rice maps of current and future climate, which were generated by the ensemble model, to create the final habitat suitability of rice. The "erase" tool in ArcGIS software was used to perform this task.

3. Results

3.1. Model Performances

Figure 3 illustrates the predictive performance of single models based on KAPPA, ROC and TSS scores. In general, the three assessment methods revealed similar results, yet the accuracy of individual models differed. The TSS evaluation showed that RF performed best (0.77 ± 0.07), followed by GBM (0.73 ± 0.11), while SRE performed worst (0.17 ± 0.09). The KAPPA evaluation results were similar to TSS, with RF performing best (0.71 ± 0.09), followed by the GBM (0.70 ± 0.17), while SRE performed worst (0.23 ± 0.12). The predictive performance evaluated by TSS and KAPPA for each model in order of performance was RF, GBM, MARS, ANN, GLM, CTA, FDA, Maxent.Phillips and SRE. The predictive performance of individual models according to ROC evaluation differed to that of TSS and KAPPA; although the RF and GBM models still performed best with the scores of 0.87± 0.08 and 0.85± 0.07, respectively, while and the SRE had the lowest score (0.57 ± 0.06). The order of performance was RF, GBM, FDA, MARS, ANN, CTA, GLM, Maxent.Phillips and SRE. The accuracy of the models was considered useful based on TSS scores, except Maxent.Phillips and SRE, which performed poorly. Finally, the ROC evaluation showed that SRE predicted poorly, while the performance of the remaining models was considered fair. The model scores of all single models are shown in Table S1 (in Supplementary material).

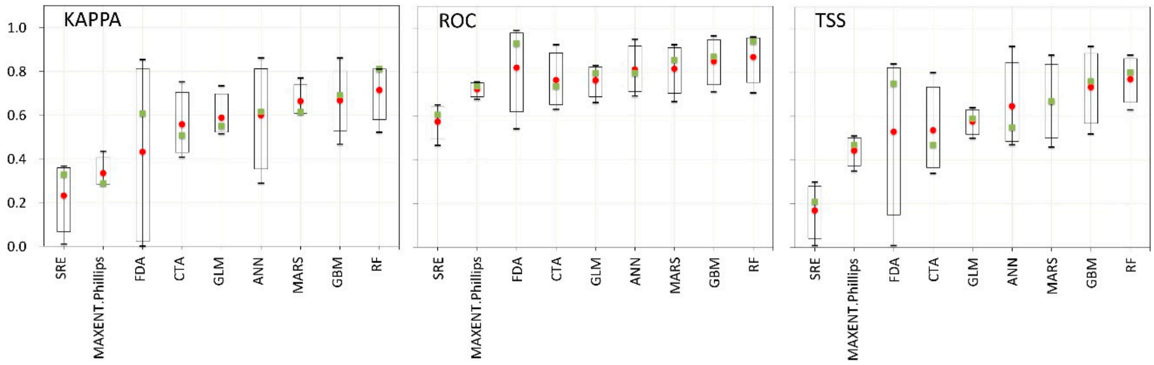

Figure 3. Performances of individual models for prediction of rice habitat suitability, in which the mean value is represented by the red circle, and the median by the green square; the open rectangle is the 1st to the 3rd quartile and the bars for the 0.1 to 0.9 percentile.

The predictive performance of the ensemble model was significantly improved in comparison to single models. The ensemble model predicted excellently based on KAPPA (0.88), ROC (0.993) and TSS (0.960) scores. The model produced sensitivity and specificity scores of 0.9604 and 0.9703, respectively. Therefore, the model correctly predicts the presence of rice at a rate of 96.04% and its absence at a rate of 97.03%.

3.2. Predictor Variable Importance

The importance level of predictor variables utilised in the ensemble model were identified (Figure S3 in Supplementary material). The potential distributions of rice are more strongly influenced by bioclimatic factors than ecological factors. Precipitation of wettest month (BIO13) had the greatest influence, followed by precipitation of coldest quarter (BIO19) and temperature seasonality (BIO4). Maximum temperature of warmest month (BIO5), minimum temperature for coldest month (BIO6) and precipitation of driest month (BIO14) also showed substantial impacts on the rice distributions while acidity, soil and precipitation seasonality (BIO15) had the least influence.

3.3. Current and Future Projections

Maps of potential distribution of rice under the current climate and RCP 4.5 and RCP 8.5 for 2050, generated by the ensemble models are shown in Figure S4 (in Supplementary material). The final habitat suitability of rice (including the consideration of salinity and SLR effects) in response to the different climate scenarios are shown in Figures 4 and 5. In the current climate, the simulation output reveals that 67.3% of land is suitable for rice cultivation, in which the optimal and moderate suitability areas accounted for 26.4% and 16.1%. The area of suitable habitat for rice cultivation dropped to 50.2% and 42.3% under the RCP 4.5 and RCP 8.5 scenarios, respectively, for the year 2050.

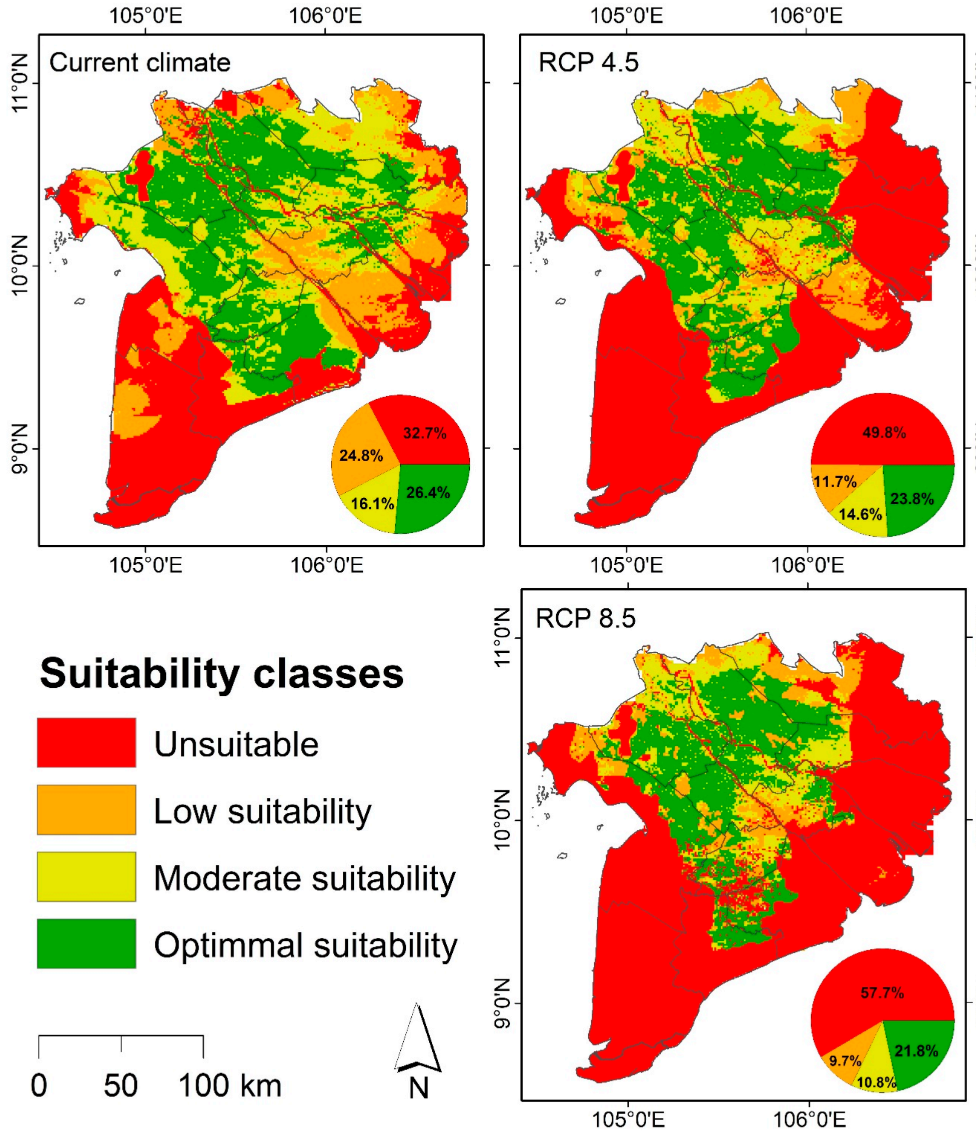

Figure 4. Habitat suitability of rice under current climate and scenarios RCP 4.5 and RCCP 8.5 by the year 2050.

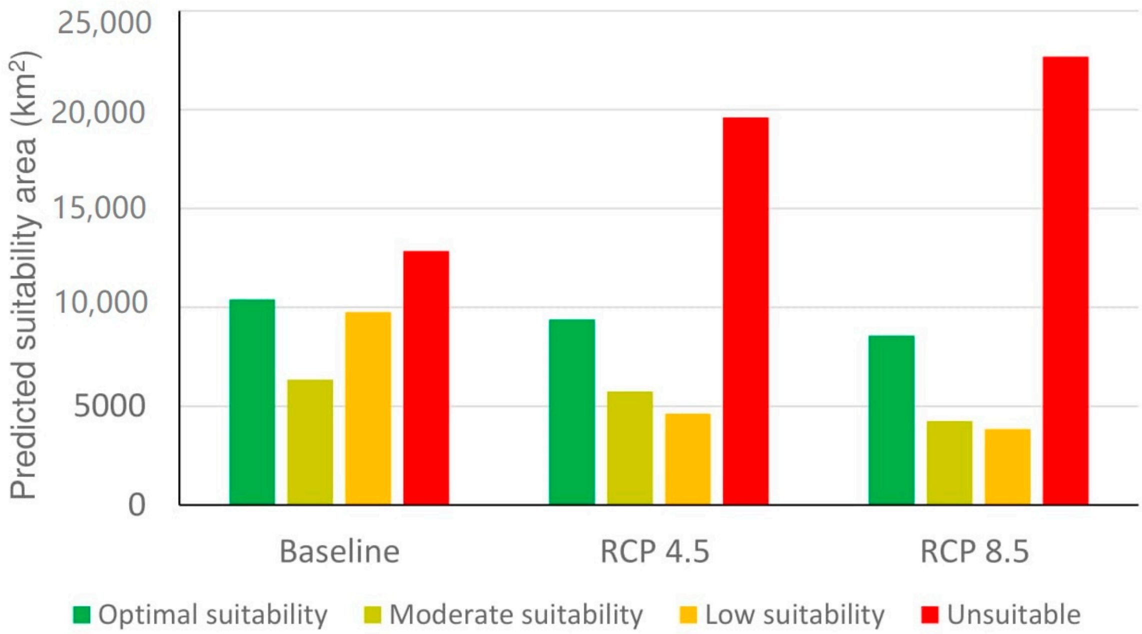

Figure 5. Current and future habitat suitability areas for rice growing in Mekong Delta under current climate and scenarios RCP 4.5 and RCP 8.5 by the year 2050.

3.4. Changes in Rice Habitat Suitability

In general, the habitat suitability for rice consistently decreased under the RCP 4.5 and RCP 8.5 scenarios for the year 2050 in comparison to current climate (Figure 6). Importantly, the drop was greater in under higher emission scenarios (RCP 8.5) than medium emission scenarios (RCP 4.5). In particular, the suitable zones for rice cultivation decreased by 25.5% and 37.2% for RCP 4.5 and RCP 8.5, respectively. Importantly, the losses of optimal suitability of land were 9.7% and 17.5% for RCP 4.5 and RCP 8.5, respectively, in comparison to the same categories in the current climate (Table S1 in supplementary material).

Figure 6 and Table 3 show the spatial shifts and quantitative changes of numerous suitability categories under the two future scenarios climate of the year 2050, in terms of unchanged, expanded and reduced. The results of spatial analysis show that the losses of suitable habitat for rice growing were considerable in areas located along the east coast of the MD due to saline intrusion. Hence, the area of land unsuitable for rice cultivation was dramatically increased by 52.6% and 76.6% under RCP 4.5 and RCP 8.5, respectively, for the year 2050.

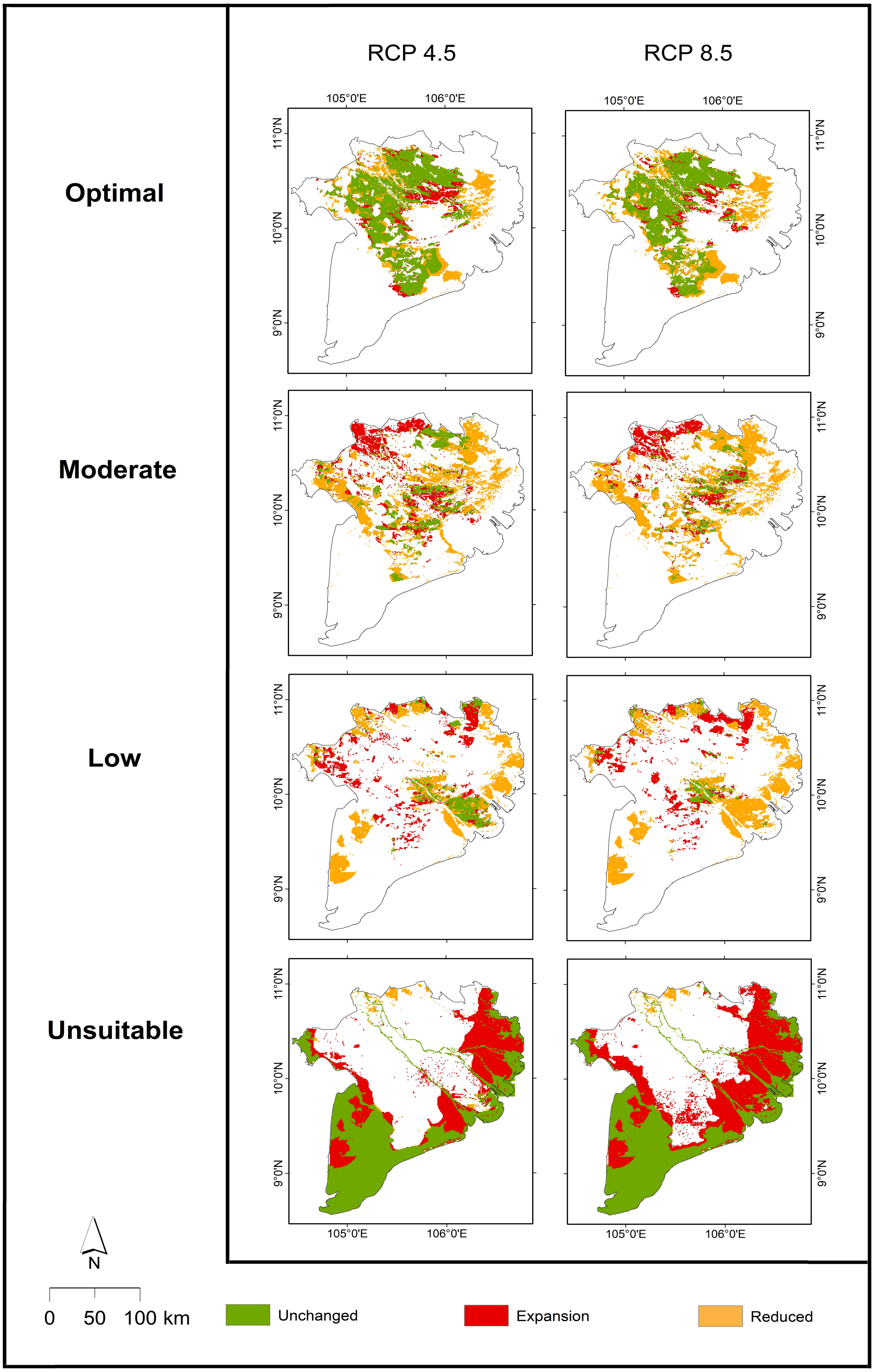

Figure 6. Change in habitat suitability zones for rice growing under current climate and scenarios RCP 4.5 and RCCP 8.5 by the year 2050.

Table 3. Changes in habitat suitability of rice by 2050 and 2070 under RCP 4.5 and 8.5 in comparison to the current suitability.

Suitability Level	Change Type	Suitability Areas (km^2) under RCP 4.5	Suitability Areas (km^2) under RCP 8.5
Optimal	Unchanged	7604 (73.2%)	7174 (69.0%)
	Expansion	1803 (17.3%)	1438 (13.6%)
	Reduced	2799 (26.9%)	3229 (31.1%)
Moderate	Unchanged	1999 (31.5%)	1512 (23.9%)
	Expansion	3701 (58.4%)	2737 (43.2%)
	Reduced	4336 (68.4%)	4821 (76.1%)
Low	Unchanged	2551 (26.1%)	1765 (18.1%)
	Expansion	2068 (21.1%)	2086 (21.4%)
	Reduced	7218 (74.0%)	8000 (82.0%)
Unsuitable	Unchanged	11,988 (93.5%)	12,213 (95.2%)
	Expansion	7439 (58.0%)	10,208 (79.6%)
	Reduced	658 (5.1%)	419 (3.3%)

4. Discussion

4.1. Model Predictions

In the current work, an ensemble model, in which a number of single algorithms were combined to generate the final ensemble model, was used to predict the potential distribution of rice. Choosing appropriate individual algorithms based on their predictive performance is very important to this process. Our results show that the predictive performances of modern machine learning approaches, including RF and GBM, were higher than other models. This result concurs with previous studies, and demonstrates the potential of these models in predicting species distributions with acceptable accuracy [42–44]. Alongside this, our finding confirms other studies [39,40,42–45] that have demonstrated the reliability and improved performance of ensemble models, providing further evidence that ensemble modelling approaches significantly improve the output of SDM in terms of model rules, and so provide a more robust approach for species distribution prediction practices.

The results on habitat suitability of rice are considered acceptable as the ensemble model indicated good predictive performance. Moreover, on the validation, the projected habitat suitability for rice under the current climate agreed well with the current distribution of rice paddy fields as determined through survey by MARD. Specifically, 98.12% of the current rice paddy fields fall within areas modelled as suitable; specifically, 49.18%, 35.58% and 13.36% were modelled as being of optimal, moderate and low suitability, respectively. This agreement indicates that the majority of existing rice cultivation areas is classified into very high, high (optimal) and moderate suitability classes in the modelling, and so indicate the robustness of model outcome. Hence, the projected land suitability for rice cultivation is considered adequately accurate since it aligns with the current rice growing areas.

4.2. Important Variables for Land Suitability of Rice

Our results show that precipitation of the wettest month and precipitation of the coldest quarter were the key bioclimatic factors that influence the distribution of rice in the MD (Figure S3). In particular, in the baseline scenarios map, rice distribution is limited in areas with very high precipitation during the wettest month. This is because high rainfall, in combination with upstream-induced flood, can cause an increase in water levels in rice paddy fields above levels that rice plants can tolerate [14]. Importantly, this excess flooding depth would affect the performance of the Main wet season and Autumn crops to the greatest degree [14]. On the other hand, lower precipitation during the coldest quarter (dry season) results in a shortage of water for rice growth and also promotes saline intrusion, and hence decreases the suitability of areas affected for rice cultivation [14,17].

Alongside this, temperature seasonality and maximum temperature of the warmest month also had strong effect on rice distribution. The map of habitat suitability for rice cultivation for the current climate revealed that the areas with extreme temperature seasonality and very high values of maximum temperature of warmest month were low suitability areas and unsuitable areas for rice cultivation. This is because the heat stress is likely to affect the growth of rice, which can combine with prolonged drought and saline intrusion to severely limit rice cultivation in the MD [13,14,17].

Soil salinity level was also one of the key contributors influencing rice growth in the region. This is because rice plant can be affected by saline water (saline concentration > 4 g/L) [17,95]. The areas located along the coast, especially the south east coast, experience saline water, and so are unsuitable for rice development.

4.3. Rice Habitat Loss Due to Climate Changes

Climatic variables critically influence growth survival and recruitment of a given species and so affect the spatial distribution of that species [97,98]. Changes to climate, which are likely to modify the distribution of species, vary according to region and GCM projections [99,100]. Thus, the projected habitat suitability for species is governed to a large degree by the GMC used in the predictive models. The present study combined different GCMs, viz GFDL-CM3, MRI CGCM3 and CNRM CM5, which were used because of their demonstrated suitability in Vietnam and in South Asia [43,44,67]. A combination of various GCMs is recommended to improve the consistency of projected climatic variables [62,63], and so the predictive results will be improved and more reliable.

The findings of the current work reveal that the distribution and extent of suitable areas for rice cultivation in the MD were considerably affected by climate change. The area of land determined to be suitable for rice cultivation decreased consistently under the two climate scenarios, RCP 4.5 and RCP 8.5, for the year 2050 compared to the current climate (Figure 5, Table 2 and Table S2). In the case of the RCP 8.5 scenario, the model predicted a decrease of 37.2% and an increase of 76.6% of suitable and unsuitable lands, respectively, compared to current climate, demonstrating the severe threat of climate change on rice cultivation in the MD. Not surprisingly, the reductions in habitat suitability for rice cultivation were greater under the RCP 8.5 scenario than the RCP 4.5 scenario (Figure 5, Table 2 and Table S2).

These reductions in the area of habitat suitable for rice production reflect several changes in seasonal patterns of rainfall and temperature. Our model shows that high precipitation during the wettest months was the major threat to rice cultivation. Critically, increases in rainfall with extreme rainfall events and periods during the wet season caused by climate change are likely to decrease habitat suitability of rice. By the year 2050, the mean rainfall for the wet season in the MD will increase by 9.1–9.5%. This increase, combined with SLR and flooding from upstream runoff will increase the maximum flood depth (meters) by 0.6–1m and 1.1–1.5m and also the duration of floods [17]. These increases in flood depth and duration are likely to affect rice production in the MD [101].

In addition to the impact of wetter wet seasons, our study found that low precipitation during the dry season also had strong effects on the suitability of areas for rice cultivation. Some areas in the MD have already been experiencing increasing shortages of fresh water for agricultural use during the dry season, and the average rainfall for the dry season is projected to decrease by a further 3.5–4.9% [17]. This further reduction in rainfall by the year 2050 will dramatically affect the agriculture practices, especially rice production, which needs more water than other crops. Climate change also increases the variability in seasonal rainfall, leading to more frequent and severe drought events and saline intrusion, which exacerbates the effects of lower rainfall and drought on rice cultivation [17].

The high temperature seasonality with extreme heat events and periods, as well as high temperature during the hottest months, also strongly affect habitat suitability for rice. By the year 2050, the average maximum temperatures in the dry season (hottest months) are projected to increase by 2–2.75 °C. This increase, combined with an increase in the severity and frequency of heat waves [14,17] will negatively affect rice growth and so limit the suitable lands for rice cultivation [17].

The maps of changes in the area suitable for rice cultivation (Figure 6) show that salinity intrusion greatly affects the suitability of habitat for rice cultivation in the MD. SLR is one of the main causes of the salinity intrusion, which is exacerbated by prolonged drought, leading to extensive damage to agricultural crops, especially the Autumn rice crops in the MD [17]. The results from the present study show that by the year 2050, substantial areas of suitable lands in the coastal zones (Soc Trang, Tra Vinh, Ben Tre, Tien Giang and Long An provinces) become unsuitable for rice cultivation due to salinity intrusion (Figure 6). Alongside this, SLR can directly inundate land and make it unsuitable for rice cultivation. However, for RCP 4.5 ad 8.5 scenarios of the year 2050 with the SLR of 22 and 25 cm, respectively, SLR-induced inundation, causing rice habitat loss was small compared to the losses of suitable habitat for rice cultivation due to climate changes and saline intrusion (Figure S2 in supplementary material).

Our results also show that some areas experienced an increase in the area suitable for rice cultivation (Figure 6) due to increased rainfall in the future climate scenarios. However, this increase is much less than the area that is subject to a decrease in habitat suitability for rice cultivation. The average loss of suitable lands and average gain of unsuitable lands were 31.4% and 64.6%, respectively, for the year 2050 compared to the current time. This finding confirms the negative impacts of climate change on rice crops that has been shown in studies conducted in other countries [35,102,103] and highlights the value of the approach taken in this study to examine the impacts of climate change on food crops [35].

4.4. Implications on the Impacts of Rice Habitat Loss on Sustainability

The present study found that climate change is severely threatening rice production in the MD showing substantial declines in the area suitable for rice cultivation under future climate scenarios. Previous studies indicated that rice production in the region is being undermined and becoming unstable due to increases in frequency and magnitude of excessive flooding, droughts and salinity intrusion caused by climate change [13,17]. Rice demonstrates phenotypic plasticity in yield-related traits with respect to various environmental conditions and, hence, rice yield is likely to be severely reduced under unsuitable environmental conditions [104]. The MD is the most significant rice production region in the country, which critically supports national food security and income [105]. Hence, the decreases in rice cultivation areas and rice yield due to climate change will severely affect food security and economy of the region and the country as well.

The decreases area suitable for rice cultivation also affects the sustainability of the region in terms of livelihoods for the community and ecosystem conservation. Rice production accounts for a large proportion (54%) of the labour force in Vietnam and for the MD [17,73]. Hence, the decrease in rice production is likely to severely threaten livelihoods of communities. Even under the current climate with severe conditions of saline intrusion, around 40% of livelihoods of communities in the MD were affected due to the damage to agriculture activities including rice production [17]. Alongside this, the losses of rice paddy lands is likely reduce the important functions of this type of wetlands in ecosystems services, such as balance and purification of water resources and provision of habitats for fauna, flora biodiversity and wild life in these fresh water ecosystems.

4.5. Recommendations on Sustainable Production of Rice in the MD

The changes in potential habitat suitability for rice obtained in the current study under different climate scenarios are a valuable resource for the development of appropriate strategies for sustainable production of rice and future planning in the MD. Several specific recommendations can be made on the basis of our findings. First, the optimal and moderate suitability land areas that will remain suitable for rice cultivation should be continuously supported with enhanced techniques for optimised rice cultivation. Second, the potential to expand rice cultivation into areas that are predicted to become suitable should be explored [33]. Third, adaptation plans, such as changes in time schedules of crops or potential alternative crops, should be developed for areas predicted to experience reduced habitat suitability.

According to our model, increases in rainfall during the wet season is a key driver of reduced suitability for rice cultivation because the higher rainfall will increase flood frequency and magnitude, which, in turn, reduce rice production. Hence, the effects of flooding on rice cultivation could be mitigated either by adjusting the time schedules between crops, so that rice growth could accommodate the flooding conditions, or by effective flood control systems. The decrease in rainfall during the dry season causing prolonged drought combined with SLR leading to salinity intrusion, will also considerably affect rice growth in the MD. To address this, appropriate irrigation systems could be useful to prevent moisture stress in rice plants. In addition, potential alternative crops and saline prevention systems could address salinity intrusion due to SLR. Adjusting time schedules of rice crops could be also useful because the salinity intrusion mainly affects these areas during the dry season, but not during the rainy season. For long-term sustainable production of rice under climate change, it is recommended to improve monitoring and early warning systems, which can provide real-time information on floods, droughts and salinity for mitigating the effects as well as developing appropriate plans for rice crops and other agriculture crops in the MD.

4.6. Study Limitations and Contribution

As with other studies using modelling approaches to predict climate change impacts on crop production, the present study has some limitations. For example, this study does not consider some non-bioclimatic factors, such as irrigation systems and land-use changes in the future of the region, which may have impacts on rice cultivation. However, the MD has high densities of rivers and canals as well as high rainfall amount due to monsoon climate, which are sufficient sources of water for rice cultivation. Hence, the absence of the irrigation systems in the model likely did not cause substantial effects on the results. Additionally, the present study only considered the effects of permanent inundation caused by SLR on rice cultivation, but not the effect of higher tides and storm surges, which may temporarily inundate and salinise lands, and so temporarily affect rice cultivation. Another limitation is the uncertainties in the GCMs used for modelling. There is no consensus on how to select the most accurate or appropriate for any one regional setting [43].

Despite these limitations, the present study critically contributes to the improvement of SDM approaches for predicting species distribution and research on the impacts of climate change on agricultural practices as well. The study demonstrates a robust approach for projection of species distribution in comparison to the prediction of single-algorithm approaches, and so significantly improves the results of ensemble models in terms of modelling rules. Our findings also provide comprehensive information on the impacts of climate change on rice production, which is a useful source for sustainable rice production and future planning for land-use management.

5. Conclusions

The current work develops a modelling approach to project the potential distribution of areas suitable for rice cultivation under current and future climate scenarios. The study found that climate change considerably affected the distribution and extent of land areas suitable for rice cultivation in the MD. Specifically, the area of land suitable for rice cultivation decreased by 37.2%, and the area of unsuitable land increased by 76.6% by 2050 under the high emissions scenario (RCP 8.5) compared to current climate. Salinity intrusion due to SLR was found to be one of the major factors responsible for the loss of suitable land. Importantly, this study provides a robust approach for investigation of the impacts of climate change on rice production in the regions.

Our take-home message for policy and decision-makers, as well as stakeholders, is that climate change impacts must be considered to sustainably manage rice cultivation practice. In particular, our results predict the spatial distribution of suitable lands for rice production and the potential for geographic shifts in optimal areas for future rice production. This information will critically support planning for rice cultivation in the future. Moreover, this spatial information, combined with environmental factors affecting rice cultivation under future climate, can further aid in developing suitable strategies, such as infrastructure development, adjustments of crop schedules and crop alteration for adaptation and mitigation in response to climate change impacts. Finally, appropriate uses, maintenance and rehabilitation of rice paddy and crucial wetland ecosystems can contribute to ecosystem protection and conservation.

Supplementary Materials: The following are available online at http://www.mdpi.com/2071-1050/12/22/9608/s1, Figure S1: Salinity concentration maps in Mekong Delta, Vietnam under current climate, and RCP 4.5 and RCP 8.5 of the year 2050, Figure S2: SLR-induced inundation maps in Mekong Delta, Vietnam under RCP 4.5 and RCP 8.5 of the year 2050, Figure S3: Variable importance. Table S1: Predictive performance of individual models for predicting potential distribution of rice, Table S2: Ecological niche for the rice distribution by current (1960–1990), 2050 and 2070 under RCP 4.5 and 8.5.

Author Contributions: A.T.N.D. conducted this study as part of her PhD Thesis under the supervision of L.K. and M.R., who also reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The authors gratefully acknowledge UNE in Australia for financial support to the first author; the Ministry of Natural Resources and Environment, Vietnam; Ministry of Agriculture and Rural Development, Vietnam; the National Remote Sensing Department, Vietnam; and Global Climate Science Team for data support.

Conflicts of Interest: The authors declare no conflict of interest.

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